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ABSTRACT

This paper develops a service optimizing model which integrates marketing and operations management issues. To address the issues related to simultaneous production and consumption of services, the optimal service model uses conjoint analysis and strategies for capacity and demand management to illustrate the interaction between a firm's market share and the waiting time of its customers. This service optimizing model provides unique advantages for solving complex service design problems over the existing product optimizing models. First, the model accounts for all relevant operations and marketing costs for demand and capacity management decisions. Second, by integrating actual customer preference data, all appropriate costs and revenues; there is a more direct link between customers' perception of service waiting time and profit to the firm than found in previous models. Finally, the model is tested and applied to an existing service, a ski resort. The example incorporates empirical data from existing customers, potential customers, and industry experts in the region. The objective is to determine the mix of capacity and demand management strategies which maximize annual profits. The results of the application show that optimal solutions involve increasing capacity and installing queue information signage while use of inter-day demand smoothing led to substantial loss in profits. Many so called "improvements" to the service, actually led to declines in service levels and hence lost profits.

1. INTRODUCTION

1.1 Motivation for the Study

Increasingly, both operations management researchers and marketers are focusing on optimal product design. The goal of this task is to determine the optimal attributes of a product or set of products. Optimal may be defined in terms of various criteria such as market share, sales, return for the firm, contribution for each product, societal welfare, or some combination of these.

From a marketing perspective, the theoretical research on product positioning models has increased dramatically in the last ten years. While these models focus on determining the optimal product attributes, they are extremely limited in terms of estimating costs for different attribute levels. Marketing researchers predominately tend to focus on market share optimizing models. Published applications of profit optimizing models, which include estimates of variable and fixed costs, have been limited to the work of Dobson and Kalish (1988; 1993), Green and Krieger (1989; 1992), Morgan (1996), and Verma (1996).

Recently, several researchers developed models that better integrate marketing and operations related costs in manufacturing environments. Morgan (1996) developed a profit maximizing model which incorporates inventory and set-up costs for optimal product line development. Although this model has not been applied in an actual industry setting, it goes a long way towards addressing the optimal product set from a firm's perspective. By including other non-marketing related factors which are affected by product line decisions, the model determines the optimal mix of products to maximize the firm's profits and the profit impact of manufacturing cost interactions with the number of products in the firm's set. However, the primary focus of her model is to determine the number of possible products to produce (i.e., focused or broad product line) rather than the appropriate attribute combinations of a particular product.

Developers of product optimizing models implicitly assume that the model is transferable to services. In many instances this assumption is not valid due to the unique nature of service encounters. Services face higher instantaneous variations in demand than manufacturing settings (Chase & Aquilano, 1995). Given this highly variable demand and the joint production between the buyer and seller, this situation can create waiting lines and crowded service facilities. Customer perception of attributes such as waiting time and congestion affect optimal facility design and offer the possibilities of time varying pricing strategies. As a service takes on more preferred attribute combinations, the demand for the service will increase, as will the customer's waiting time under constrained capacity conditions. Thus, in a service optimizing model, one should consider both the buyer's and seller's waiting time and costs for the provided service level. The buyer's costs include waiting and actual service time; the seller's costs include the time in the service transaction, other costs related to service delivery, and long term costs of unsatisfied customers. Because both parties attempt to minimize their transaction costs, matching supply to extremely variable demand becomes major challenge for the service provider.

In a recent article on integrating marketing and operations research, Karmarker (1996) stresses that marketing issues cannot be decoupled from operations and production issues in services. He indicates that operations strategy research has ignored marketing issues with the exception of pricing, while service marketing research has ignored the concurrence of production and consumption. Karmarker and Pitbladdo (1995) indicated that service models must go beyond the usual price-quantity economic models. While several authors have discussed the importance of simultaneously evaluating capacity and demand strategies for optimal service design, few researchers have modeled or empirically tested these ideas to determine the appropriate strategy (Antle & Reid, 1988; Fitzsimmons & Fitzsimmons, 1994; Karmarker, 1996; Sasser, 1976).

The model proposed in this paper attempts to overcome the previous deficiencies by including relevant *demand* issues such as customer preferences and segmentation, product positioning, and pricing, as well as *operations* issues such as capacity planning, technology choice, and associated cost relationships. It builds on product positioning models (e.g., Green and Krieger (1985; 1992)), concepts from general pricing and capacity decision models (e.g., Karmarker and Pitbladdo (1995) and Stidham (1992)), and costing and capacity models (e.g., Davis (1991) and Maggard (1981)). Its objective is to determine the mix of demand and capacity strategies which optimizes the profit for the service provider while accounting for the customer's utility for different attributes of the service system, including waiting time, price, and other physical attributes. The model is then used for actual decision making in a complex service network environment, a ski resort, to determine the optimal strategy for expansion and improvements.

1.2 Organization

The paper is divided into five sections. Section 2 reviews the relevant literature. Section 3 outlines the proposed service optimizing model. The model is applied to an actual problem dealing with capacity and demand strategy decisions for a ski resort in Section 4. Section 5 provides the results of the ski resort problem. Finally, Section 6 summarizes the research, limitations, and future opportunities for this type of approach.

2. LITERATURE REVIEW

Few researchers have focused specifically on optimal service design. The first section discusses optimal product models. The general category of product design optimization problems includes single product design, multiple product design or product line selection, and simultaneous product line design and selection problems. The section covers the three basic approaches to modeling and solving optimal product(s) problem using multidimensional scaling (MDS), conjoint analysis (CA), and quality function deployment (QFD). The second section of the review outlines models which address problems unique to services such as capacity and pricing, capacity and costing, and capacity and demand matching.

2.1 Optimal Design of New Products

Several researchers have addressed the design of optimal products in the last 10 to 15 years. The research stream has three major approaches. MDS and CA are popular techniques for marketing researchers with emphasis on pricing and attributes of products. QFD has received attention from both marketing and operations management researchers due to the integration of customer preferences with operational capabilities. MDS and CA assume that preference for a product can be related to the customer's perceptions and preferences for the product's underlying attribute levels relative to those of competing products (Green & Krieger, 1989). Similarly, the theory behind QFD assumes that by identifying and integrating customers needs and preferences into the entire product development process, customer satisfaction follows (Hauser & Clausing, 1988).

Green and Krieger (1989) summarized optimal product and service design problems:

1. What type of new or reformulated product should be introduced into an existing competitive array?
2. What type(s) of single product or product line should be introduced sequentially or simultaneously into the competitive array?
3. What is the optimizing objective of the firm: market share, sales revenue, return on investment, etc.? Does the objective include cannibalism of existing products?
4. Will the market dynamics include competitive retaliation?

5. Which design constraints influence feasible attribute levels such as technology or costs?

6. Should buyers be differentially weighted in the objective function according to purchase frequency?

2.1.1 Quality Function Deployment

While the other optimal product design methods have a distinct product attribute or marketing orientation, quality function deployment (QFD) is one of the few methods which tries to link the design of products or services with the processes that produce them. Thus, it would appear that QFD is a more appropriate approach for optimal services design because services consist of product and process features.

QFD is a formal management process in which the 'voice of the customer' is incorporated throughout all stages of product development (Griffin, 1992; Griffin & Hauser, 1993; Hauser & Clausing, 1988). Through QFD's systematic approach, the customer's needs and perceptions of existing products are linked (1) to design attributes of a product, (2) from design attributes to possible actions the firm can take in terms of component changes, (3) from actions to implementation (i.e., changes to a manufacturing process), and (4) from implementation to production planning (Griffin & Hauser, 1993).

Each stage of QFD analysis uses a house of quality (Hauser & Clausing, 1988) with the following layout: customer requirements for product attributes and perceived importance make up the left side; perceptions of how the product compares to competition comprise the right side; the ceiling of the house has engineering characteristics, the roof of the house has interactions between engineering characteristics; the bottom of the house contains objective engineering measures of existing products, projected costs and technical difficulty of changing a design attribute; and the center matrix of the house shows how the engineering characteristics are likely to affect customer attributes.

Griffin and Hauser (1993) found that interviews with a small group of customers, 20-30 individuals, could identify 90 percent or more of customer attributes or needs for a homogeneous segment. The authors measured customer's perceptions of their chosen product with respect to these needs and regressed those perceptions on customer's satisfaction with that product. The revealed preferences did not correlate with either preference or interest in the concepts. This finding suggests that direct elicitation of attribute importance is somewhat inferior to other market research techniques such as conjoint analysis. However it should be noted that Srinivasan (1988) found larger predictive validity with a conjunctive-compensatory or a two state self-explicated technique compared to conjoint analysis.

On the other hand, Griffin (1992) found that 29 out of 35 project teams believed that QFD provided definite strategic product development benefits, particularly improving the ability to structure cross-functional group decision making, team building and motivation, and information flows between different users.

Kim, Moskowitz, Dhingra, and Evans (1993) proposed an integration of fuzzy multi criteria methodologies with QFD. With this approach, product designers could consider tradeoffs between various customer attributes while accounting for the inherently vague and imprecise nature of these relationships.

While QFD is an important tool for encouraging interaction and communication between functional groups, as typically applied the method lacks a systematic way to maximize economic returns to the firm. Instead, the goal is achieving average customer needs and preferences given the capabilities of the firm. This research draws on the basis of QFD by accounting for capabilities and the voice of the customer but additionally proposes a method to meet the objective of maximized return for the firm.

2.1.2 Multidimensional Scaling

Shocker and Srinivasan (1974) initially outlined a method for optimal product positioning using MDS, a framework wherein customer product preferences are represented as ideal points in a perceptual space. The space is referred to as joint space, because it contains both products and customers. In the space, perceptual dimensions are comprised of several underlying attributes developed from discriminate analysis or other methods (e.g., the dimension, *quality*, would be comprised of several other attributes such as reliability, timeliness, and durability).

The ideal points (i.e., most preferred attribute combinations) are mapped on to the joint space according to customer's preferences for different products. The *i*th customer's preference for the *j*th product, π_{ij}, can be modeled as some function of the Euclidean distance between the *j*th product and *i*th customer's ideal point:

where:

$$\pi_{ij} = f\left(\sum_{k=1}^{A}(I_{ik} - Y_{jk})^2\right), \tag{1}$$

I_{ik}	=	the ideal point for the *i*th customer on the *k*th dimension,
Y_{jk}	=	the location of the *j*th product on the *k*th dimension,
A	=	the number of dimensions in the MDS joint space.

Generally, a model using MDS has a goal of locating a new brand in the joint space so as to maximize sales, market share, or profit.

Two MDS-based optimal product design models, first choice and probabilistic, were originally proposed by Shocker and Srinivasan (1974). The first or deterministic choice method, assumes that each consumer will choose the product closest to his/her ideal point. Therefore, a new product is located in joint space so that the product is closest to the maximum number of ideal points. The probabilistic choice model, assumes that choice probability is an inverse function of the relative distance of the product point to a customer's ideal point.

There have been several methods to determine an optimal solution in multidimensional space. These include grid searching or gradient searching (Shocker & Srinivasan, 1974), branch and bound approach (Albers, 1979; Albers & Brockhoff, 1977), and other surface searching methods (Gavish, Horsky, & Srikanth, 1983). Sudharshan, May, and Shocker (1987) compared these methods in several different environments and found that algorithm performance, measured in terms of product point preference share relative to the highest value obtained by any algorithm, is sensitive to (a) the number of customers or segments, (b) probabilistic versus deterministic choice, and (c) the number of existing products. All methods exhibited poorer performance as the number of customers or competing products increased. Those methods with the ability to model probabilistic choice outperformed those with deterministic choice only.

Green, Carroll, and Goldenberg (1981) and Green and Krieger (1989) point out several problems with the MDS approach. They include measurement of manipulable dimensions, data collection required to create a corresponding multidimensional space, large computational time, and difficulties in achieving global optima. Computational time and global optima solutions are relatively minor problems compared to those associated with dimension measurement and data collection .

2.1.3 Conjoint Analysis

Conjoint Analysis, CA, attempts to determine the value that consumers place on various attributes or features, by evaluating individual reactions to a set of hypothetical product descriptions. There are two broad types of conjoint analysis: ratings-based and choice-based. In ratings-based experiments, consumers provide stated purchase likelihood evaluations for hypothetical products viewed one at a time. In choice-based experiments, individuals pick a product from a set of hypothetical choice alternatives. For either case, a collection of hypothetical profiles is generated from a fractional factorial design, using statistical design theory, or from a full factorial design. The pattern of choices or likelihoods generated by the respondent is then used to generate a consumer utility function of the underlying product characteristics:

$$U_{ij} = \sum_{l=1}^{L} \beta_{il} x_{lj} , \tag{2}$$

where:

U_{ij}	=	the buyer *i*'s overall utility of product alternative *j*,
β_{il}	=	the buyer *i*'s utility weight associated with attribute level *l*,
x_{lj}	=	the level of attribute *l* in alternative *j*,
L	=	the total number of attributes.

Zufryden (1979) defined the optimal product problem in terms of consumers' utilities. Given a set of J competitive profiles $\{X_1, ..., X_J\}$, find the profile X_k such that U_{ik} is greater than U_{ij}, j = 1, ... , J for the greatest number of customers. Later, he extended this approach to optimal product line design (1982).

Green, Carroll, and Goldberg (1981) used a probabilistic approach, a powered Bradley-Terry-Luce share-of-utility rule (BTL), which is able to mimic several different choice rules to predict customer preferences. From individual ratings-based conjoint experiments, the probability of buyer *i* selecting product *j* is given by:

$$\pi_{ij} = \frac{U_{ij}^{\alpha}}{\sum_{j=1}^{J} U_{ij}^{\alpha}}, \tag{3}$$

where:

U_{ij}	=	the utility of customer *i* for product *j*,
α	=	an exponent (α= 1 for BTL rule; large α for maximum utility rule),
J	=	the total number of suppliers or competitive products.

Similarly, choice-based experiments generate a utility function for the aggregated group of customers so that π_j, the probability that product *j* is chosen from among the members of set *J*, is defined by a basic Luce (1959) or multinomial logit model (MNL) as:

$$\pi_j = \frac{e^{U_j}}{\sum_{j=1}^{J} e^{U_j}}. \tag{4}$$

Used in a consumer choice simulator, these buyer utilities predicted market share, dollar volume, and contribution to overhead and profit for various hypothetical product profiles X_j. The problem of selecting the optimal product is generally formulated as follows:

$$\underset{X_j}{Maximize} \sum_{s=1}^{S} N_s \, \pi_{sj} \left(P_j - V_j \right) - F_j , \tag{5}$$

where:

N_s	=	the number of customers in market segment s,
S	=	the number of market segments, $s \in S$,
π_{sj}	=	the probability that a person in market segment s will choose profile X_j from among the members of profile set J,
P_j	=	the price for profile X_j,
V_j	=	the variable cost associated with profile X_j,
F_j	=	the fixed cost associated with profile X_j.

The goal of the formulation is to determine the product profile X_j that maximizes the objective. By sequentially setting $F_j = 0$, $V_j = 0$, $P_j = 1$, and $N = 1$; the problem becomes one of maximizing contribution, revenue, unit sales, or market share, respectively.

Green and Krieger (1985) extended this formulation to the optimal product line selection. In their two step method, the program selects a subset of k products from the original set of candidate products, J. Using an iterative reselection and replacement scheme, some best subset of test products is selected. Due to the combinatorial complexity of the problem, solutions require the use of heuristic procedures such as greedy, interchange, and Lagrangian relaxation.

More recently, Green and Krieger (1989; 1992) developed SIMOPT, a product positioning model with more extensive features. First, the program has provisions for using one of several buyer choice rules (e.g., deterministic rule, logit choice rule, and share of choice rule or probabilistic choice). Second, market shares or returns for each competitive brand are included with adjustments for base-case market share levels. Third, optimal products are determined by maximizing market share or return. Fourth, the individual preference models developed from CA can be used to generate different market segments. Finally, the model incorporates costs or returns by having the user assign costs for each level x of attribute l. SIMOPT has the ability to model independent direct variable costs at the individual-attribute level and interaction costs (Green & Krieger, 1991). The optimizing heuristic, a divide-and-conquer variety, finds the best combination of a subset of attributes then evaluates other subsets through a complete cycle, continuously repeating until no better solution is found.

Many authors have expanded on the product line development approach to include other criteria in the objective function and additional constraints which reflect more realistic conditions, such as fixed and variable costs, similar product efficiencies, and cannibalization. As the complexity of the problems increase, researchers have focused on developing faster and more efficient heuristic applications.

For example, Dobson and Kalish (1988; 1993) modified the objective function to maximize profits by positioning and pricing each product in a product line. In this case the firm's problem is to determine which k products to introduce at what price p to maximize total profit. The model for the profit version is:

$$\mathit{Maximize} \quad \sum_{s=1}^{S}\sum_{j=0}^{k} n_s(p_j - v_j)x_{js} - \sum_{j=1}^{k} f_j y_j , \tag{6}$$

subject to:

$$\sum_{j=0}^{k} x_{js} = 1 , \tag{7}$$

$$x_{js} \leq y_j , \tag{8}$$

$$\sum_{j=0}^{k}(u_{sj} - p_j)x_{js} \geq (u_{sj} - p_j)y_j , \tag{9}$$

where:

Data Variables

v_j = the constant variable cost for product *j*,

f_j = the fixed cost of product *j*,

x_{js} = integer (0 or 1) representing assignment of product *j* to segment *s*,

y_j = integer (0 or 1) representing the offering of product j,

u_{sj} = the utility of the *s*th segment for the *j*th product,

n_s = the number of customers in segment *s*,

S = the total number of customer segments,

Decision Variables

p_j = the price for product *j*,

k = the number of products considered.

The objective function (6) represents the total contribution to profits from the product line after subtracting the fixed costs. Constraint (7) ensures that exactly one of the available products is assigned to a customer segment. Constraint (8) ensures that only products assigned to customer segments are included in the product line. Constraint (9) requires that the overall utility for each customer segment for its offered product is greater than for any other products. Because the problem is non-linear and NP-complete, the authors propose solving the model with greedy heuristics. In this context, state of the art heuristics have been reviewed by Kohli and Sukumar (1990). More recently, several authors have proposed other heuristics for generating close to optimal or good solutions to the product design problem. Nair, Thakur, and Wen (1995) employ a beam search heuristic while Balakrishnan and Jabob (1996) evaluate the performance of genetic algorithms.

Generally, the product optimization literature has focused on the appropriate price and attributes while cost issues have been simplified to either fixed or linear functions of attribute levels. Similar to these approaches, the service optimizing model developed in this study accounts for the increasing complexity in realistic design optimization situations. Services consist of product and process attributes with interdependencies creating non-linearities and step functions, thus solution procedures will often involve heuristic approaches or complete enumeration.

2.2 Services

Service 'products' have unique attributes that deserve special attention. Because services involve (a) joint production between buyer and supplier and (b) lack inventory, there are special consequences for service competition, markets, pricing and contracting, and strategic management of services (Karmarker & Pitbladdo, 1995). While certain services have the ability to inventory using reservations and yield management (Kimes, 1989; Weatherford & Bodily, 1992), this paper is concerned with such services without reservation capabilities. For these services, increased market share or demand can create situations of congestion and subsequent customer dissatisfaction.

Furthermore, joint production and perishability require that service providers optimize a more complex function covering both service product and process attributes. Marketing decisions, such as variations in price, product, and promotion and expected demand adjustments from these decisions, interact with process attributes such as facilities configuration. Similarly, operational decisions, such as capacity changes, scheduling, and process improvements, affect customer waiting time and costs of service delivery.

In the next section, we review the relationships between marketing and capacity attributes. We then note the implications of these relationships for modeling optimal services. Next we review the relationships between capacity and its related costs with subsequent implications for the optimal service model.

2.2.1 Marketing and Capacity

Process attributes such as congestion and waiting are a function of the relationship between existing capacity and demand for the service. Demand that exceeds supply leads to waiting time and congestion, which costs the buyer, while supply that exceeds demand costs the seller. Therefore, service optimizing models must account for the level of demand-to-supply 'matching.'

The service time t_j in any service encounter usually depends on the specific service configuration or layout, the customer arrival rate (partly a function of the popularity of the service), service capacity, and time variability of demand. Little previous research has attempted to link service time to capacity and price with the exception of the work by Stidham (1992), who formulated a service problem from a queuing perspective to determine the optimal pricing and capacity for a service facility. His model assumes a single server queue in steady state, in which arrival rate λ (a proxy for price) and service rate μ (capacity) are design variables.

Karmarker and Pitbladdo (1995) proposed the joint production model for a monopolistic service supplier. In this case, the service output is assumed to be a deterministic function of the time spent by both parties in the production of the service. The price charged for the service is a function of the division of labor between the two parties and the buyer has a utility for his or her portion of the service time.

2.2.2 Costing and Capacity

Joint production models illustrate that capacity carries a cost to the buyer and seller (Karmarker & Pitbladdo, 1995). From the seller's perspective, overall service costs depend on the time and cost spent providing the service. From an operations management perspective, this cost translates to the number of workers scheduled or level of capacity investment. On the other hand, the buyer has costs for time spent in the system, which correspond to his or her preferences. These costs would include lost time from paying work or other preferred activities. Maggard (1981) and Davis (1990) translate these buyer costs to the seller's perspective by linking waiting time to customer dissatisfaction and estimated loss of future profits for the firm. Therefore from the firm's perspective, the goal is to minimize the sum of capacity costs and loss of future profits from unsatisfied customers.

3. OPTIMAL SERVICE DESIGN MODEL

As a preliminary approach to addressing appropriate variables for a service model, Karmarker and Pitbladdo's (1995) joint production model for a monopolistic service supplier can be extended to a competitive environment. In this extension, we incorporated a logit model with J competitors and N potential buyers in each market segment *s*. The new model is:

$$Maximize: \sum_{s=1}^{S} N_s \pi_{sj} (P_j - c_j t_j) - F_j , \qquad (10)$$

such that:

$$\pi_{sj} = \frac{e^{U_{sj}}}{\sum_{k=1}^{J} e^{U_{sk}}} , \qquad (11)$$

$$U_{sj} = \beta_{st} t_j + U_{s'j} , \qquad (12)$$

where:

Data Variables

N_s = the number of potential buyers in the market segment *s*,

c_j = the service *j* cost per unit time to serve a customer,

F_j = the fixed costs for service *j*,

U_{sj} = market segment *s*'s overall utility for a service *j*'s attributes,

$U_{sj'}$ = market segment *s*'s overall utility for a service *j*'s attributes other than service time e.g., Equation (2),

β_{st} = market segment *s*'s perceived attractiveness weight for t_j.

Decision Variables

t_j = the average customer's service time in service encounter for service *j*,

P_j = the price for service *j*.

The objective function (10) represents the total contribution to profits from the service after subtracting its fixed costs from the contribution margin that accounts for the variable costs of the customer's service time. Equation (11) gives the probability that a given segment will purchase the service. Equation (12) defines the utility function for the segment that is a function of the average customer's service time and other attributes.

While the above model addresses the marketing variable, price, and the operations level variable, service time, it is limited in application to simplistic service design problems where there is a linear relationship between waiting time and service cost, and capacity fixed costs are independent of service time. While the model includes price, several other marketing attributes have been used to adjust demand to a given level of capacity in a service. The field of marketing has long studied how marketing mix variables can influence their customers' perceived utilities for products. If utilities are assumed to be related to demand, supply to demand matching can be affected by variations in the service marketing mix. These include variations in product, information communication, and modification of timing and location of service delivery (Lovelock, 1992). Price variation strategies use different prices to level the demand, such as offering lower off-peak rates to move customers to less busy periods. Product variation strategies offer different products during different periods to encourage customers to utilize the service during slow periods, such as offering egg sandwiches in the morning at fast food restaurants. Information strategies attempt to provide customers with advance information about least crowded periods or shorter waiting times, to encourage customers to utilize these slow periods or facilities. Strategies that modify the time and place of delivery use techniques such as extended hours and mobile services to flatten demand peaks or increase sales.

The service model proposed in the next section uses joint production in a competitive environment to design optimal service facilities. It addresses demand/capacity variation by including marketing and operations related variables affecting waiting time. An assumption of this model is that for a given service and capacity level, different marketing strategies influence customer utility via marketing mix attributes (such as price) and these in turn affect overall demand and consequently customer waiting time. By incorporating a customer's utility for waiting and other service attributes, we can determine the resulting affect on expected market share and profit for a firm in a competitive environment. This model attempts to account for: (1) profit shifts due to changes in customer waiting time and (2) capacity costs to achieve different customer waiting times.

To use the model, one must assume a base-line service configuration with an existing or forecasted demand pattern for the service and estimated customer utility data relevant to the particular service. The existing conditions for a particular service in a competitive market are explicitly defined (e.g., number of customer segments, number of customers in each segment, existing service price, fixed costs for the service, variable cost for service attributes, and a target service level). The service level refers to the percentage of all customers that wait less than a certain time. The operations management decision makers can adjust capacity to different service levels for a specified customer waiting time with a corresponding capacity cost to achieve the service level.

3.1 Demand/Capacity Variation Model

For services consisting of both variable customer demand and an inability to utilize reservation systems, service design strategies that attempt to match demand and capacity levels offer many possible solutions. The goal of a demand variation strategy is to shift demand from periods of excessive facility utilization to those of underutilization. On the other hand, the objective of a capacity variation strategy would be to adjust capacity to meet demand patterns. In this model, we are considering three types of demand variation strategies: price, customer class mix, and information; and two types of capacity variation strategies: expansion with new facilities and upgrading existing capacity with improved technology.

Services with enough capacity to meet average demand usually experience three different time periods of capacity utilization: underutilization (slower than average days or periods within the day with idle capacity); excessive utilization (busier than average days or periods within the day with lengthy waiting lines and fully occupied capacity), and acceptable utilization (average days or periods within the day meeting the target service level requirements). For this model, we have assumed a constant set of market segments, but vary the number of people in each segment according to the time and their ability to participate in demand variation strategy. For example, movie theaters may offer afternoon matinee discounts, but only certain movie viewing segments have the ability to attend during those hours. Similarly, ski resorts offer discounts on weekdays and during certain winter weeks, but many customers are constrained to the weekend days and traditional vacation periods.

Depending on the strategies implemented, the elements affected are price, variable and fixed costs, number of people in each segment, and customer's waiting time. The problem of selecting the combination of demand and supply matching strategies that maximizes the total profits to the firm is formulated as follows:

$$\underset{X_j}{Maximize} \sum_{g=1}^{G} \sum_{h=1}^{H} y_g z_h \left[\sum_{m=1}^{M} T_m \sum_{s=1}^{S} N_{sT_m} \pi_{sj} \left(P_{jhm} - V_{jg} \right) \right] - F_j - \sum_{e=1}^{E} \sum_{r=1}^{R} \sum_{w=1}^{W} x_e a_r q_w C_{erw}, \quad (13)$$

such that:

$$\pi_{sj} = \frac{e^{U_{sj}}}{\sum_{k=1}^{J} e^{U_{sk}}}, \quad (14)$$

$$U_{sj} = \beta_{sP} P_{jhm} + \beta_{st} t_j + U_{s'j}, \quad (15)$$

$$t_j = f\left(SL_j, z_h, x_e, a_r, q_w, \lambda, \mu \right), \quad (16)$$

$$\sum_{g=1}^{G} y_g = 1,\ \sum_{h=1}^{H} z_h = 1,\ \sum_{e=1}^{E} x_e = 1,\ \sum_{r=1}^{R} a_r = 1,\ \sum_{w=1}^{W} q_w = 1\ , \qquad (17)$$

where:

Data Variables

T_m = the number of time periods with capacity utilization *m*,

M = the number of different capacity utilization levels, $m \in$ M,

H = the number of different pricing variation strategies, $h \in$ H,

G = the number of different customer class variation strategies, $g \in$ G,

S = the number of market segments, $s \in$ S,

E = the number of different capacity expansion strategies, $e \in$ E ,

R = the number of different capacity replacement strategies, $r \in$ R,

W = the number of different waiting line information strategies, $w \in$ W,

N_{sTm} = the number of customers in segment *s* during time periods T with capacity utilization *m*,

π_{sj} = the probability that market segment *s* will choose service *j* out of k =1, ... , J choices,

U_{sj} = market segment *s*'s overall utility for a service *j*'s attributes,

$U_{sj'}$ = market segment *s*'s overall utility for a service *j*'s attributes other than those affected by strategy decisions,

P_{jhm} = the price of service *j* using price variation strategy *h* during period *m*,

V_{jg} = the variable cost per person for service *j* using customer class variation strategy *g*,

F_j = the fixed cost for service *j*,

C_{erw} = the fixed capacity costs using capacity expansion strategy *e*, capacity replacement strategy *r*, and waiting line information strategy *w*,

β_{sP} , β_{st} = the market segment *s*'s perceived attractiveness weight for P_{jhm} and t_j,

λ = the customer interarrival rate,

μ = the service rate,

Decision Variables

y_g = 1 if customer class variation strategy *g* is used, 0 otherwise,

z_h = 1 if pricing variation strategy *h* is used, 0 otherwise,

x_e = 1 if capacity expansion strategy *e* is used, 0 otherwise,

a_r = 1 if capacity replacement strategy *r* is used, 0 otherwise,

q_w = 1 if waiting line information strategy *w* is used, 0 otherwise,

t_j = the waiting time in service *j*,

SLj = the target service level in service *j*.

The objective function (13) represents the total contribution for time periods T_m. The fixed costs for the service product and capacity costs to achieve a certain service time are subtracted from the contribution. In this particular model, the capacity strategy costs are assumed to be fixed costs independent of time periods, T_m. Equations (14) and (15) give the market share estimates and the customer segment utility with the service attributes affected by the strategies, respectively. Equation (16) provides the relationship between service time, target service level, chosen strategies, interarrival rate, and service rate. The set of constraints in (17) ensure that only one strategy level is assigned per approach, including the option of no variation, level 1 for all strategies.

3.3 Solution Approaches

The service model can be solved through complete enumeration or heuristic procedures depending on the number of: available strategies, variable service attributes, and capacity adjustments. The general procedure for solving the problem requires five steps provided below:

3.3.1 Procedure

1. Using historic demand data or forecasts, input (1) the number of time periods corresponding to underutilization, overutilization, and acceptable utilization during the year, T_m where $m = 1,\ldots, M$ different levels of utilization (e.g., M=3 if all three levels are used), (2) the number of price variation strategies H and the prices P_{jhm} corresponding to each service profile, pricing strategy, and utilization level, (3) the number of customer class variation strategies and the variable costs V_{jg} associated with each strategy, and (4) the number of capacity expansion, E; capacity replacement, R; and waiting line information, W, strategies; with their respective costs C_{erw}. Set feasibility constraints for the problem such as budget, capacity expansion and demand limitations, etc.

2. Collect market survey information using choice-based or ratings based-conjoint analysis. Using multinomial logit model (choice-based surveys) or multiple regression (ratings-based surveys) and an appropriate segmentation method, determine the number of customer segments S and the utility weights, β_{sl} for customer segments and service attributes L. Input the utility weights, β_{sl}, and fixed attributes for service (those attributes not affected by capacity, wait time, and price variations), $U_{service} = \Sigma\, \beta_{sl}X_s$. Assign all competitors an expected utility based on actual or perceived attributes.

3. Determine the relationship between (a) different combinations of demand and capacity variation strategies and (b) peak or average wait time, using either queuing theory models for stable service environments or discrete event simulation for transient service conditions.

4. The combinatorial problem can be solved with one of the following methods depending on the size of the problem: (a) <u>Complete Enumeration</u>: Generate

solutions to the problem using full factorial design with complete enumeration. Evaluate all possible solutions and pick the maximum profit solution or (b) Heuristics: Other potential solution approaches include simulated annealing or tabu search heuristics to generate near-optimal solutions.

5. In either case, the following procedure is used to match wait time to demand; (a) start with the existing service design profile and determine the market share for the existing configuration using the MNL model. Calibrate the MNL model by reweighing all competitors using actual market share values. Then, (b) pick a new service profile and estimate each market segment's utility for the service profile using a minimum wait time for the chosen service profile, MWAIT, (c) calculate the new market share and estimated number of people going to the service, (d) search the simulation or queuing model results from Step 3 for the expected wait time, EXWAIT, for the service profile under the new growth level, and (e) if EXWAIT $\leq$ MWAIT, (i.e., the actual wait time for the service profile is less than or equal to the wait used to calculate the market share) use the predicted market share in the profit objective function otherwise increment MWAIT in step (5b) and iterate until reaching the equilibrium wait point.

4. APPLICATION

In this section, we apply the service specific model to an optimal service design problem. Specifically, the demand/capacity variation model is used in a complex service environment to determine the appropriate strategies for simultaneously managing demand and capacity at a ski resort in Utah. The previous product optimizing models could not account for the impact of capacity to demand mismatches on the customer's time in the service, which is often a complex non-linear relationship. Waiting time for lifts is usually a significant attribute in a ski customer's utility model. Any permanent demand or capacity change will affect most customers' service time, this new time will change the customers' utility for the service, and consequently overall demand by the segmented or aggregated customer market. Thus, these changes affect the business' profitability.

A ski resort is a complex service network environment due to the existence of multiple facilities - ski lifts and restaurants - and their corresponding queues. The customers pay a basic fee to enter the system, may visit each facility perhaps multiple times or may not visit it at all, and usually pay additional fees for certain facilities. Each lift's technology determines its capacity (e.g., traditional two person chairs versus high speed quad systems).

Although the national number of skier-days (number of customers skiing or snowboarding in one day) has remained level since 1978, skier-days in the Rocky Mountain region have increased 16 % between 1979 and 1995 (NSAA, 1995). Researchers estimate that Utah has experienced an average of 5% skier growth annually from 1979 through 1991 with a shift from a locally dominated population to an increasingly national and international ski population (Jones, 1991). Additionally, the snowboarding population, the fastest growing activity of winter sports, is expected to double by the year 2000 (Economist, 1993). Appealing to the younger age groups (11-25 yrs) , which comprise a large proportion of the western US population, snowboarding has significantly affected the current resort demand. McCune (1994) indicates that several successful resorts have increased revenues by targeting markets with older skiers and beginning skiers. According to her research, these marketing efforts have affected the operational costs at those resorts because the ski terrain must be maintained at increased levels for those skiers.

All Rocky Mountain resorts face varying constraints on capacity due to environmental regulations that limit their acreage and parking areas, surrounding public lands, natural rugged terrain, and snowmaking capability. On the other hand, to be a contender in this market, a resort must continually improve the facility by installing chair lifts, adding trails, and keeping up with the latest snow-making technology (McCune, 1994).

4.1 Research Objectives

The ski resort studied, Powder Valley (disguised name), competes against six other contenders in a regional market. Half of the other resorts have made recent investments in facility improvements in the last five years. The ski resort we investigated had observed a decline in ticket sales, which management attributed to their competitors' improvements. Therefore, based on interviews with resort management, the following research questions were posed:

1) What are the possible demand or market based strategies to increase demand in or shift demand to underutilized periods such as weekdays and early or late season days? Correspondingly, what types of strategies will shift demand to underutilized facilities within the resort? What are the expected costs and benefits of each particular strategy?

2) What are the feasible capacity additions and their respective costs to the resort?

3) What is the relationship between the proposed strategies and peak waiting time in the resort?

4) What are the appropriate market segments, their preferences for different attributes of the service, and estimated segment sizes?

5) Assuming no change in the competitors' offerings, what changes to the existing resort should be implemented to maximize annual profit?

4.2 Empirical Data Collection

The data for this study were collected from these sources: interviews with management at the resort and competing resorts in the region, statistics from industry groups, regional marketing research studies, customer surveys at the resort, observation of the existing service system, and simulation of hypothetical configurations.

4.2.1 Interview Data

The existing industry and firm specific information was gathered from several sources. Costs for resort improvements, expansion constraints, and marketing information was obtained from interviews with the management group at the resort. The marketing manager estimated the impact of variations in pricing strategy based on previous implementation of similar programs. The resort provided daily demand information for the past ten years.

For a more accurate indication of the entire ski market numbers, interviews were conducted with management representatives from other ski resorts and statistics collected from the Utah Travel Council, regional and national ski organizations..

4.2.2 Customer Utilities and Segmentation

For the present case, attributes and levels were developed from focus groups of skiers in the region, as part of a larger study sponsored by the U.S. Forest Service (Louviere & Anderson, 1994). According to their study, consumers' preferences for resorts can be described in terms of 13 attributes: physical setting, distance from home, snow base, new snow, vertical drop, types of runs, size of area, challenge mix, facilities, ticket price, peak lift-line wait, types of lifts, and snowboards allowed/not allowed. Louviere and Anderson (1994) developed the choice sets used in the discrete choice analysis for the customer preference model in this study. The questionnaire was sent to 1200 regional skiers. By the cutoff date, 276 completed surveys were returned.

Although the ski industry can be segmented by a number of demographic factors, Green and Krieger (1991) found that behavioral or preference segmentation provided optimal market share and profit results. Therefore, in this study, the individual customer choice data were used to generate customer preference segments. Respondents are segmented according to a K-means algorithm. As described by Punj and Stewart (1983), the method involves *a priori* setting the number of clusters, then clustering individuals according to their part-worths after first centering an individual's data around the mean. Initially, a case is assigned to a cluster and then reassigned to the cluster whose centroid is closest to that case. The reassignment continues until every case is assigned to the cluster with the nearest centroid. The objective is to minimize the within cluster variance.

All models were run on LOGIT (Woodworth, Gilbert, & Fox, 1990) for the aggregated individual data, a two segment model, and a three segment model. To determine which the segment level models was the best fit, we used Akaike's (1974) information criterion (AIC) to determine the appropriate number of segments. Using this criteria, the three segment model minimized AIC and was used in the above procedure.

After determining the appropriate number of segments, industry experts provided interpretations of the customer segments based on the important attribute weights (e.g., hard-core skiers, family destination skiers, and variety seekers) and the number in each market segment during busy versus slow days.

The utilization periods, T_m, were determined from existing capacity and demand. For this study, skiers underutilized weekdays and overutilized weekends and holidays. No days were defined as "adequately utilized" thus the model had only two types of utilization, with T_1 and T_2 representing the total of slow and busy days per average year, respectively. Industry experts provided opinions on potential market size for each segment for each utilization period (e.g., the potential market size for national holidays is twice the size of winter weekdays).

4.2.3 Customer Surveys

Customer surveys were distributed to approximately 500 individuals skiing at the resort during winter season 1996. The survey is included in Appendix 1. Customers identified their skiing ability, demographics, and traffic pattern for the day. This information was used to generate a database of lift choices as a function of skiing ability, arrival and departure time distributions, lunch and ski day duration distributions.

4.2.4 Strategy Combination Impacts on Waiting Times

Due to the complexity of a ski resort service design, we created and validated a simulation model (Pullman & Thompson, 1997) to find the peak waiting time for customers using the different strategy and demand combinations. The simulation program was developed using FORTRAN 77 and run on a SUN Microsystems workstation. The user can input the following parameters for any ski resort configuration: the probability and average speed of different skier classes (e.g., beginner to expert) traveling between lifts, the speed and capacity of all the existing lifts and possible future lifts, and historic data or forecasted skiers for each day of ten hypothetical years (six average years, two high demand years, and two low demand years). The existing configuration was validated with waiting line data from sample days and long-term customers' and managers' assessments.

Two type of decision variables are examined in the simulations, (1) those that fall directly under management control, endogenous variables, and (2) those that are largely exogenous variables. Endogenous variables include: replacing lift capacity with increased uphill capacity (speed and seats), expanding lifts into new terrain, and installing waiting time information signage. Exogenous variables include: growth in existing demand, change to the customer class mix, and smoothing demand by moving more weekend skiers to weekdays. Powder Valley considered the following combination of specific options: replacing one to three existing lifts with upgraded technology, expanding skiable terrain into a new area with an additional lift, and installing signage information for waiting lines. These options occur under the exogenously determined scenarios, three levels of yearly demand (current demand, 5 % greater than current demand, and 20 % greater than current demand), two customer class mixes (existing and increased percentage of beginners and intermediate skiers), and two smoothing strategies (none and evenly dispersing 10 % of weekend skiers to the weekdays).

The simulation program runs through the same set of hypothetical days for all ten years so that results are comparable between configurations. We felt that running the program for ten years would more adequately represent the weather and customer demand variations that occur at ski resorts. After running through 1500 days, the program determines peak waiting time experienced by 90 percent of all customers (e.g., 10, 20, 30, 40, and 50 minutes and greater than 50 minutes). This percentage was the service level used to compare all strategies.

4.3 Market Share Adjustments and Wait Time Solution Approach

Using the existing configuration as a baseline, the market share is evaluated for the resort. This calculated share is adjusted to account for the actual share according to the method proposed by Green and Krieger (1992) where the adjusted market share is given by:

$$\pi^*_{sj} = \frac{w_s \pi_{sj}}{\sum_{j=1}^{J} w_s \pi_{sj}} \tag{18}$$

where:

w_s	=	the reweighing constant = $I_s / (\pi_{s\,base})$,
I_s	=	the initial actual market share of supplier *s*,
$\pi_{s\,base}$	=	the estimated initial market share for supplier's existing configuration,
π_{sj}	=	the estimated market share for supplier's new configuration *j*.

As the market share increases due to customer preferences for different configurations, the procedure program checks to see if the target service levels can still be maintained. The simulation was run for the following levels of overall demand increase at the resort: none, 5 %, and 20% increase from the existing demand. For each growth level, the program determined the peak wait time under all combinations of strategies. Because it was infeasible to run all possible growth levels, in cases where we needed to determine the wait time for a growth of 10% or 18%, the appropriate wait is determined from interpolation between known values.

5. RESULTS

Tables 1- 3 present peak waiting time results from the simulation using three sample growth levels. These tables illustrate that as growth increases, many of the strategy configurations can not maintain the same peak waiting time. For example, if the resort simply expands the terrain, the peak waiting time stays at 20 minutes through 5% growth but deteriorates to 40 minutes with 20% growth. Conversely, by installing two new lifts and queue information signage, the resort can maintain the optimal service level of less than 10 minute peak waits through 20% growth.

5.1 Aggregated Model Example and Results

Table 4 provides the aggregate utility weights for ski resort attributes. Consumer's most important attributes are price (t = -21.5996) and lift line wait (t = -11.7638). Looking at the beta coefficients, lift line wait has a negative coefficient (-0.1919) implying that as lift line wait increases, consumer's utility for the resort will decrease. Relevant to this research, this preference implies a drop in market share with increased lift wait time.

5.5.1 Example of Procedure

STEP 1. Table 5 provides the resort's prices and costs and assumptions for the different strategies.

STEP 2. Using the model information provided in Table 4 and the actual attributes of all competitors, the model predicts an existing market share of 18% for Powder Valley.

STEP 3 & 4. The relationships between strategies and peak waiting times are provided in Tables 1-3. These relationships were determined from the simulation model with complete enumeration of the full factorial design as previously discussed

STEP 5. (a) Although the model predicted an 18% market share for the resort, the actual market share is 12.81%. Therefore subsequent market share results are reweighed to account for this difference. (b) We assign the resort a new configuration: two new lifts, a signage system, and set the minimum wait time, MWAIT, at 10 minutes. After modifying the appropriate attributes for Powder Valley and using the aggregate utility weights from Table 4, the utilities for the seven competitors are: U_1=0.72, U_2 = 1.08, U_3 = -0.66, U_4 = -0.78, U_5 =0.11, U_6 = 0.86, and U_7 = 0.67 (Powder Valley Resort = 5). (c) Powder Valley's new reweighed market share is 15.42% or a 2.61% increase in market share from the original value. The 2.61% increase in market share corresponds to 77,117 skier-days in an overall regional market of 2,954690 skier-days. Correspondingly, the 77,117 skier-days increase represents a 20% growth to the resort itself with 378,641 existing skier-days. (d) After searching the simulation results from STEP 3, the expected peak wait time for the new configuration with 20% growth, EXWAIT, equals 10 minutes. (e) The expected wait, EXWAIT, of 10 minutes is less than or equal to MWAIT, the wait time used to calculate the market share. Therefore the predicted market share, 15.42%, is the equilibrium value to use in the profit objective function. The new profit for the resort is $11.74 million. If the expected wait had not met the limit criteria, MWAIT would be incremented by 1 minute and the program would iterate from step (b) until that equilibrium wait time was determined.

5.5.2 Aggregate Model Results

Tables 6 and 7 show profit solutions for the aggregated model found with the procedure. If there are no changes to exogenous variables, optimal profit occurs when the resort installs two new chairs and queue information signage. This scenario was used in the example above. Although demand increases, the new resort configuration had the ability to maintain a 10 minute peak wait time for 90% of the customers through the 20% demand increase. Thus the existing market share solution is feasible and the resulting profit gains are approximately $1.67 million per year above the existing configuration.

After examining changes to the exogenous variables, several points are evident. First, the demand smoothing strategy leads to a reduction in profit, regardless of any endogenous variable changes. For example, when the resort uses the interday smoothing strategy and installs two new lifts, they experience a $10 contribution margin reduction from weekday skiers and if the existing waiting time could be maintained, a 20% increase in demand. Unfortunately, the waiting time can only be maintained through 6% growth without service level deterioration. This small demand improvement is not enough to counter the revenue loss from the smoothing strategy and the cost of installing the two lifts. Second, if the customer class mix changes, generally the resort makes a better profit than that achieved from the existing customer class mix. The exceptions occur when terrain is expanded and resort queue information is installed. In that case, the profit is less if more than one lift is installed. With a different customer class mix, the optimal solution involves upgrading one chair lift leading to a profit gain of $ 0.81 million per year over doing nothing at all. In conclusion, it appears that the most profitable solution for the aggregate model implies no attempts to adjust exogenous variables via demand smoothing or customer class changes.

5.2 Segment Level Model Results

Table 8 provides the utility weights for the three segments, the optimal number according to AIC criteria. The segments are interpreted as follows: segment 1, variety seeking skiers, are the least price and waiting time sensitive, want a full resort experience (i.e., skiing is not the most important activity), and prefer all types of terrain; segment 2, hard core skiers, are most sensitive to wait time and price, prefer lots of snow, vertical elevation, most difficult terrain and steep slopes, and high speed quad lifts, but do not want snowboarding allowed; segment 3, family skiers/snowboarders, are sensitive to price and lift wait, prefer mixed terrain and ability levels, and are neutral about snowboarding.

The results for the segment level model are provided in Tables 9 and 10. Similar to the aggregated model, the optimal configuration occurs with two new lifts and information signage with no changes to exogenous variables. In this case, the resort makes \$1.96 million more per year in profit relative to the existing configuration (e.g., \$12.18 million vs. \$10.22 million). This model shows similar patterns to the aggregated model, endogenous and customer class mix changes contribute to profit improvement. Maximum improvements come from simultaneously installing new lifts and installing information signage. Again, the customer class mix variation outperforms the existing class mix with the same exceptions noted previously, while demand smoothing reduces profits in all cases. The optimal solution with the segment model market, \$12.18 million, exceeds the optimal solution in the aggregated model, \$11.74 million, for the same configuration. This difference occurs because the largest population in the segment model market is segment 2, hard core skiers, who are the most waiting time and high speed quad sensitive. Thus, changes to these attributes increases the probability that these skiers go to Powder Valley above the average or aggregate level.

6. DISCUSSION

In this section, we present a discussion of the model, limitations of the study, future opportunities for this approach, and conclusions.

6.1 The Model

This paper has introduced a model for optimal service design that accounts for the interaction between customers' waiting time and increased demand on a service system. By simultaneously addressing waiting time and costs related to demand and capacity management strategies, the service model provides a unique advantage over previous product design models. The model was applied to potential management decisions for an actual service environment. This example highlighted the linkage between (1) creating a more desirable service by reducing customer's waiting time and providing other desirable attributes, and (2) having an appropriate demand or capacity management strategy to maintain the waiting time under increased demand conditions. The most profitable service design balanced wait time, other service attributes, demand growth, and the cost to achieve these improvements.

In the example used in this paper, we assumed that competitors did not change their service attributes, the resort's prices remained at a certain level, and customers have knowledge of the resort's waiting line performance versus its competitors. While the model has the capabilities to include competitive or dynamic changes and evaluate different pricing for optimal profits, it is not clear how long it takes for waiting time changes to affect demand for the service.

6.2 Limitations of the Study and Implications for Future Research

To implement the service model, the user must make certain assumptions about the relationship between customer demand and waiting time. This relationship can be relatively straightforward for simple service applications such as a drive-in window at a fast food restaurant, typically a simple queuing model. On the other hand, more complex services, such as the example provided in this paper where the arrival rate varies both by time of day and type of day and where there are multiple servers, often require simulation modeling to appropriately replicate the behavior of the system. Additionally, depending on the number of capacity and demand management decisions available to management, the combinatorial problem can involve extensive model building capabilities and computational time unless the solution method utilizes heuristics. Future research could investigate solving larger combinatorial problems with heuristics.

The second limitation relates to the nature of integrative models. Because services usually represent a joint production effort between the business and the customer, the model requires extensive empirical data from both parties. As was illustrated in this research, the model required CA survey information for the resort's competitive attributes, customer preferences for attributes within the system and the timing of these preferences, and management inputs on costs and price for various strategies.

A third limitation concerns the static nature of the model. This model is based on the maximum market share growth for the particular configuration. Thus, we have assumed that the firm reaches the market share level quickly and maintains this position. In reality, this growth could occur over a several year period until reaching the target depending on diffusion of waiting line information or consumer's knowledge of new technologies at the service. To speed the diffusion of this information, we may need to account for increased promotional expenses. Similarly, the service may chose to make the capital improvements in installments instead of replacing two lifts in one year or a promotional campaign that aims to change the customer class mix may take several years to have the desired effect. We have not accounted for competitive retaliation in the industry or possible changes to the utility functions if customers decide that certain attributes are more important over time. Future research should attempt to model these dynamic factors.

This model is limited to those services where waiting time is a significant attribute for customers. In certain cases, the service can use waiting lines as places to provide entertainment thus nullify the negative perceptions. Obviously, if waiting time is not an important attribute relative to other attributes for a particular service, then it is independent of demand growth. In which case, existing product optimizing models offer more appropriate methods for determining the optimal service design.

While this model addressed fixed capacity or "lumpy" improvements, many services have variable capacity such as the number of servers working during a certain time period. Future research could extend this model to include services with both fixed and variable capacity issues. An example of this type of service is a bank with ATM machines and tellers. Here the model could integrate labor scheduling issues with machine capacity investments.

Finally, services are not unique in competing on time. Many manufacturers achieve a competitive advantage by competing on delivery time and throughput time. In these environments, increased demand potentially leads to both increased delivery time and throughput time unless capacity increases accordingly. Future research could attempt to account for these time elements by modifying the proposed service model for these types of manufacturing situations.

6.3 Conclusions

This paper developed a service optimizing model with previously neglected features appropriate to services competing on waiting time. The model extends prior research in optimal product design. It is the first model to address and empirically test issues related to the concurrence of production and consumption in complex service design. The research highlights the flaws in using existing optimal product models for services where customer-waiting time is an important attribute. By making a more desirable service product, demand is increased.

Therefore, service models must account for increased capacity costs and demand impacts on the customer waiting time attribute, e.g., the costs and revenues associated with maintaining a certain level of demand to supply matching.

The study advances the service operations strategy literature by addressing the strategic capacity design problem from the firm's perspective, in this case, simultaneously evaluating marketing and operations management costs and decision trade-offs. Few researchers have empirically tested these ideas to determine an appropriate strategy. This research evaluates multiple combinations of marketing and operations strategies at an existing service and determines the optimal combination of strategies for the firm. Our findings illustrate that often decisions made by one functional area, such as attempts to change the composition of the customer segments, will negatively impact other areas of the firm, cause a drop in service level, and lead to lost profits for the firm.

The model proposed in this research offers more realistic capabilities than previous capacity models. While other models in the management or marketing literature have addressed service capacity, none of these models adequately assess the capacity problem from a realistic firm's perspective. First, previous pricing and capacity models have two major limitations: (a) the firm assumptions are extremely limited and unrealistic for most real services, i.e., monopolistic supplier (Karmarker & Pitbladdo, 1995) and single server queue in steady state (Stidham Jr., 1992) and (b) either no costs (Stidham Jr., 1992) or limited costs (Karmarker & Pitbladdo, 1995) are included in the models. Our model can be used for any service in a competitive environment with any number of competitors and all relevant costs can be included. Second, previous costing and capacity models (Davis, 1991; Maggard, 1981) must make assumptions about the cost of waiting time as it relates to lost future profits for the firm. In our model, customer actual perceptions of waiting time are part of their utility function, hence directly related the market share for the firm. Hypothetical changes to the waiting time affect market share and thus profits.

This approach provides a more direct link between waiting time and profit than the previous models.

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Table 1: Peak Wait Time for 90% of Customers with No Growth

Capacity Changes		No Inter-day Demand Smoothing		Use of Inter-day Demand Smoothing	
		No Resort Queue Information	Resort Queue Information	No Resort Queue Information	Resort Queue Information
No New Terrain	0 new lifts	20	20	20	10
	1 new lift	20	10	20	10
	2 new lifts	20	10	10	10
	3 new lifts	10	10	10	10
Expand Terrain	0 new lifts	20	10	20	10
	1 new lift	20	10	20	10
	2 new lifts	20	10	10	10
	3 new lifts	10	10	10	10

Table 2: Peak Wait Time for 90% of Customers with 5% Growth

Capacity Changes		No Inter-day Demand Smoothing		Use of Inter-day Demand Smoothing	
		No Resort Queue Information	Resort Queue Information	No Resort Queue Information	Resort Queue Information
No New Terrain	0 new lifts	30	30	20	20
	1 new lift	20	10	20	10
	2 new lifts	20	10	20	10
	3 new lifts	20	10	20	10
Expand Terrain	0 new lifts	20	20	20	10
	1 new lift	20	10	20	10
	2 new lifts	20	10	20	10
	3 new lifts	20	10	20	10

Table 3: Peak Wait Time for 90% of Customers with 20% Growth

Capacity Changes		No Inter-day Demand Smoothing		Use of Inter-day Demand Smoothing	
		No Resort Queue Information	Resort Queue Information	No Resort Queue Information	Resort Queue Information
No New Terrain	0 new lifts	40	60	40	50
	1 new lift	40	30	40	20
	2 new lifts	30	10	30	10
	3 new lifts	30	10	30	10
Expand Terrain	0 new lifts	40	40	40	30
	1 new lift	40	20	40	10
	2 new lifts	30	10	30	10
	3 new lifts	30	10	30	10

Table 4: Aggregated Utility Weights for Ski Resort Attributes

Variable	Beta Coefficient	T value
Intercept	0.2435	2.3612
Drive Time	-0.1414	-8.6898
Drive Time ^{2}	-0.0172	-1.8599
Snow Base	0.0896	5.4126
Snow Base ^{2}	-0.0091	-1.0207
Lift Line Wait	-0.1909	-11.7638
Lift Line Wait ^{2}	-0.0037	-0.4160
New Snow	0.0308	5.6173
New Snow ^{2}	-0.0024	-2.4592
Vertical Drop	0.0086	2.0669
Number Runs	0.0068	.3316
Number Runs ^{2}	0.0001	.0119
Price	-0.0697	-21.5996
Price ^{2}	-0.0004	-1.1881
Difficulty Level 1	0.0463	.7918
Difficulty Level 2	-0.0876	-1.5945
Difficulty Level 3	-0.0464	-0.8957
Setting Level 1	0.2080	3.3628
Setting Level 2	-0.0834	-1.3302
Setting Level 3	-0.0754	-1.3030
Terrain Level 1	-0.0167	-0.2864
Terrain Level 2	-0.0238	-0.4079
Terrain Level 3	0.0433	0.7097
Facility Level 1	-0.0492	-0.7884
Facility Level 2	0.0835	1.3868
Facility Level 3	0.0784	1.3210
Lift Types Level 1	0.0258	0.4041
Lift Types Level 2	0.0279	0.4515
Lift Types Level 3	0.0601	1.0197
Allow Snowboarding	-0.0279	-0.7649

Table 5: Variable Inputs for Service Profiles

Variable	Input
T_1 Time periods overutilized	56 days
T_2 Time periods underutilized	99 days
P_1 Average Price	\$ 33
P_2 Off Peak Price	\$ 23
V_1 Variable cost/customer (current customer class mix)	\$ 6
V_2 Variable cost/customer (varied customer class mix)	\$ 3
Cost Replacement Lift *	\$248,117
Cost Expansion Terrain*	\$310,147
Cost Information Signage *	\$ 62,029
Market Overall Demand/year	2954690 skier-days
Actual Resort Demand/year	378641 skier-days
Busy /Average Day Demand ratio	2:1
Other Fixed Costs	\$0

* yearly cost amortized over 15 years at 9% interest

Table 6: Profit for Aggregated Market Model with Current Customer Class Mix (Million Dollars)

Capacity Changes		No Inter-day Demand Smoothing		Use of Inter-day Demand Smoothing	
		No Resort Queue Information	Resort Queue Information	No Resort Queue Information	Resort Queue Information
No New Terrain	0 new lifts	10.22	9.18	7.71	7.65
	1 new lift	10.37	10.07	8.52	8.46
	2 new lifts	9.73	**11.74**	7.95	9.60
	3 new lifts	9.48	11.49	7.70	9.36
Expand Terrain	0 new lifts	10.30	10.24	8.46	8.20
	1 new lift	10.06	9.99	8.21	9.54
	2 new lifts	9.42	11.43	7.64	9.29
	3 new lifts	9.17	11.18	7.39	9.05

Table 7: Profit for Aggregated Market Model with Customer Class Mix Variation (Million Dollars)

Capacity Changes		No Inter-day Demand Smoothing		Use of Inter-day Demand Smoothing	
		No Resort Queue Information	Resort Queue Information	No Resort Queue Information	Resort Queue Information
No New Terrain	0 new lifts	10.38	10.32	8.59	8.53
	1 new lift	**11.19**	11.13	9.40	9.34
	2 new lifts	10.94	10.88	9.15	9.39
	3 new lifts	10.69	10.63	8.90	9.14
Expand Terrain	0 new lifts	11.13	11.06	9.33	9.27
	1 new lift	10.87	10.81	9.09	9.03
	2 new lifts	10.63	10.57	8.84	9.08
	3 new lifts	10.38	10.32	8.59	8.80

Table 8: Segmented Utility Weights for Ski Resort Attributes

Variable	Beta1	T value	Beta2	T value	Beta3	T value
Intercept	.008788	.05	.470898	2.62	.578417	2.62
Drive Time	-.032587	-1.20	-.109851	-4.04	-.338868	-8.49
Drive Time ^{2}	.002337	.14	-.012452	-.78	-.089539	-4.29
Snow Base	.019627	.70	.201557	7.06	.001824	.05
Snow Base ^{2}	.007776	.50	-.031848	-2.06	-.020315	-1.03
Lift Line Wait	-.097381	-3.54	-.275403	-9.52	-.287049	-7.85
Lift Line Wait ^{2}	.006652	.43	-.027572	-1.79	.002487	.13
New Snow	.029832	3.06	.049955	5.46	.054417	4.24
New Snow ^{2}	-.003411	-1.97	-.002696	-1.58	-.001502	-.66
Vertical Drop	-.003982	-.55	.036027	4.99	-.001547	-.16
Number Runs	.115131	3.15	-.086182	-2.52	-.053971	-1.14
Number Runs ^{2}	-.009423	-.43	.031989	1.48	-.028707	-1.02
Price	-.028944	-5.70	-.109861	-17.21	-.081197	-11.03
Price ^{2}	.000095	.16	-.002341	-3.58	.000725	.94
Difficulty Level 1	.013742	.13	-.107759	-1.11	.336760	2.57
Difficulty Level 2	-.054677	-.59	-.159017	-1.65	-.030367	-.25
Difficulty Level 3	.042251	.46	-.351673	-3.86	.310224	2.69
Setting Level 1	.385477	3.64	.054782	.53	.361603	2.52
Setting Level 2	.361894	3.51	-.432425	-3.92	-.477026	-3.37
Setting Level 3	-.052319	-.53	-.161474	-1.53	-.019942	-.15
Terrain Level 1	-.057013	-.58	-.016847	-.15	.259423	2.04
Terrain Level 2	-.063376	-.63	-.063822	-.63	-.056234	-..42
Terrain Level 3	-.113463	-1.06	.166282	1.57	.168142	1.24
Facility Level 1	-.113361	-1.02	.015689	.15	-.236086	-1.64
Facility Level 2	.285484	2.69	.108148	1.06	-.169918	-1.25
Facility Level 3	.215773	2.21	.095199	.88	-.180704	-1.34
Lift Types Level 1	.085291	.78	-.264116	-2.25	.148675	1.02
Lift Types Level 2	.016032	.15	-.018229	-.17	.197279	1.42
Lift Types Level 3	-.078697	-.78	.161781	1.58	.307610	2.39
Allow Snowboarding	-.028121	-.45	-.121667	-1.94	-.006402	-.07

Table 9: Profit for Segmented Market Model with Current Customer Class Mix (Million Dollars)

Capacity Changes		No Inter-day Demand Smoothing		Use of Inter-day Demand Smoothing	
		No Resort Queue Information	Resort Queue Information	No Resort Queue Information	Resort Queue Information
No New Terrain	0 new lifts	10.22	9.15	7.65	7.72
	1 new lift	10.29	10.21	8.46	8.96
	2 new lifts	9.73	**12.18**	7.96	9.97
	3 new lifts	9.49	11.93	7.71	9.72
Expand Terrain	0 new lifts	10.23	10.17	8.40	8.17
	1 new lift	9.98	10.60	8.15	9.91
	2 new lifts	9.42	11.87	7.65	9.66
	3 new lifts	9.18	11.62	7.40	9.41

Table 10: Profit for Segmented Market Model with Customer Class Mix Variation (Million Dollars)

Capacity Changes		No Inter-day Demand Smoothing		Use of Inter-day Demand Smoothing	
		No Resort Queue Information	Resort Queue Information	No Resort Queue Information	Resort Queue Information
No New Terrain	0 new lifts	10.35	10.29	8.57	8.51
	1 new lift	**11.16**	11.10	9.37	9.31
	2 new lifts	10.91	10.85	9.13	9.46
	3 new lifts	10.66	10.60	8.88	9.21
Expand Terrain	0 new lifts	11.10	11.03	9.31	9.25
	1 new lift	10.85	10.79	9.06	9.00
	2 new lifts	10.60	10.54	8.82	9.15
	3 new lifts	10.35	10.29	8.57	8.80

Appendix I

SKI DIARY

We are surveying customers to determine the ski traffic patterns for the resort. Please try and recall as accurately as possible, the runs and lifts you have used so far today. If you can't recall the name of the run, tell us the difficulty rating (beginner, intermediate, or advanced). We will provide a trail map to assist you in this process.

* If you took any breaks at mountain restaurants, please indicate when, where, and the approximate length of the break (in minutes).

Thank you for participating in this survey

1) Are you snowboarding or skiing today ?:
   A) Skiing ______
   B) Snowboarding ______

2) Please check your skiing or snowboarding ability (check only one):
   A) Beginner ______
   B) Advanced Beginner ______
   C) Intermediate ______
   D) Advanced Intermediate ______
   E) Expert ______

3) Please check the type of pass you are using today (check only one):
   A) Season Pass ______
   B) Coupon Book ______
   C) Day Pass (Limited Chairs) ______ Half Day Pass (Limited Chair) ____ AM or PM
   D) Day Pass (All Chair Lifts) ______ Half Day Pass(All Chair Lifts) ____ AM or PM
   E) Multi-day Pass ______
   F) Other ______

4) Please indicate your home/residence location:
   A) Salt Lake Area (within 45 minute drive) ______
   B) Utah location ____________________ ______
   C) Out of State location ______________ ______

5) Arrival Time at resort today: __________ AM/PM

6) Arrival Time at First Lift: __________ AM/PM

7) Did you stop for lunch today? Yes / No If so, what time? _________ AM/PM

8) If you have finished skiing for the day, what time did you stop skiing? _________ AM/PM

(Please turn over page)

If you are filling this out during lunch time; start with your first lift this morning.

First Lift	Run Name(s) or Ability Level	Restaurant Break? Where?

Second Lift	Run Name(s) or Ability Level	Restaurant Break? Where?

Third Lift	Run Name(s) or Ability Level	Restaurant Break? Where?

Fourth Lift	Run Name(s) or Ability Level	Restaurant Break? Where?

Fifth Lift	Run Name(s) or Ability Level	Restaurant Break? Where?

Sixth Lift	Run Name(s) or Ability Level	Restaurant Break? Where?

Seventh Lift	Run Name(s) or Ability Level	Restaurant Break? Where?

Eighth Lift	Run Name(s) or Ability Level	Restaurant Break? Where?

Ninth Lift	Run Name(s) or Ability Level	Restaurant Break? Where?

Tenth Lift	Run Name(s) or Ability Level	Restaurant Break? Where?

Thanks for your help. Please feel free to add comments here ! ! !

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